Individual-Based Artificial Ecosystems for Design and Optimization

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ABSTRACT

Individual-based modeling has gained popularity over the last decade, mainly due to its proven ability to address a variety of problems, including modeling complex systems from bottom-up, providing relationships between component level and system level parameters, and relating emergent system level behaviors from simple component level interactions. Availability of computational power to run simulation models with thousands to millions of agents is another driving force in the wide-spread adoption of individual-based modeling. In this paper, we propose an individual-based modeling approach to solve engineering design and optimization problems using artificial ecosystems (AES). The problem to be solved is "mapped" to an appropriate AES consisting of an environment and one or more evolving species. The AES is then allowed to evolve. The optimal solution *emerges* through the interactions of individuals amongst themselves and their environment. The fitness function or selection mechanism is internal to the ecosystem and is based on the interactions between individuals, which makes the proposed approach attractive for design and optimization in complex systems, where formulation of a global fitness function is often complicated. The efficacy of the proposed approach is demonstrated using the problem of parameter estimation for binary texture synthesis.

Categories and Subject Descriptors

I.6.5 [**Simulation and Modeling**]: Model Development—*Modeling methodologies*

General Terms

Algorithms, Design, Experimentation

Keywords

Individual-based modeling, optimization, markov random fields, parameter estimation, artificial ecosystem

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1. INTRODUCTION

Individual-based modeling refers to the class of analysis tools, in which the system being analyzed is modeled as a collection of autonomous, goal driven, interacting entities called individuals or agents. The interactions of the agents with each other and their environment, lead to system level behaviors, called "emergent" phenomena, which are not readily predictable even with the complete knowledge of the behaviors of the agents. This kind of bottom-up modeling approach was first proposed by Von Neumann [15] as Cellular Automata (CA). In CA, each cell's current state depended on its own previous state and its neighbors' states. These simple rules and local interactions result in some fascinatingly complex global patterns [28]. Several seminal contributions to individual-based modeling approaches were made as early as the late 70's including Schelling [30], and Granovetter [17], who analyzed problems in social science from an individual-based perspective. Axelrod [20], presented an individual-based variation of the prisoner's dilemma to study the circumstances under which a selfish agent would spontaneously cooperate and Reynolds [4], presented an individual-based local interaction scheme to replicate grouping behavior in animals. Over the last decade, there has been an increasing interest in individual-based modeling especially in social sciences [9, 14, 21], and ecology [31, 32]. This increase is mainly due to the advantages that individual-based modeling offers over traditional differential or difference equation based modeling, including explicit inclusion of individual variation [8], ease of expressing relationships between individuals, and the ability to demonstrate emergent phenomena [21] that is individual-based models (IBMs) allows the modeler to study the relationship between adaptive behavior and emergent properties [32].

Ever increasing demand for better capabilities, performance, and scalability is driving engineering systems to new complexities. Interconnections and interdependencies among these complex systems only add to the difficulties in designing them. Although several approaches are in practice for the design and analysis of complex systems [35] such as iterative maps, statistical mechanics, neural networks, system dynamics [13], and evolutionary techniques [5]. Currently used evolutionary techniques are loosely based on the principles of evolution but ignore many aspects of evolution which make it a powerful force capable of creating astonishingly complex and adaptive systems. Preservation of good solutions (elitism), maintenance of a pool of good solutions (diversity preservation) are explicitly specified in these techniques. Reproduction (crossover) is also accomplished by selecting the best available solutions. These mechanisms are useful in particular situations where the fitness landscape (solution space) of the problem is well defined and known a priori but would not be useful in situations where little or no information about the fitness landscape is available. In these situations algorithms which do not need an explicit enforcement of fitness and reproduction mechanisms are needed.

Individual-based modeling has been used to study a variety of problems across disciplines including population dynamics [7, 12], predator-prey dynamics and co-evolution [25], migration [10], ecological resource planning [3], epidemiology [22], human systems [6, 9], anthropology [29], artificial societies [14], and urban planning [24]. In this paper, we present a framework for design and optimization using evolving individuals in artificial ecosystems. The problem of parameter estimation for texture synthesis is addressed using an artificial predator-prey ecosystem as an illustration of the proposed methodology.

2. INDIVIDUAL-BASED ARTIFICIAL ECOSYSTEMS

Individual-based modeling of an ecosystem involves relating population-level dynamics to individual traits and behaviors. In this section we introduce the proposed methodology, and discuss the relationships of several population level processes to their individual counterparts.

Ecology is defined as the study of systems (called ecosystems) comprising of biological entities (biotic) functioning together with non-living physical matter (abiotic) of the environment. Several mathematical treatments of popular natural ecosystems such as predator-prey, host-parasite, host-pathogen, co-evolution, ecological niche, cooperation, food-web models exist [1]. The proposed methodology uses closed adaptations of these natural ecosystems, to solve engineering design and optimization problems. The term closed ecosystem refers to an ecosystem which is self-sustaining. Resource exchange between the closed ecosystem and external environment is assumed to be non-existent.

Population dynamics is one of the most important ecological processes. In a closed ecosystem, each of the species' population dynamics has to exhibit some form of equilibrium. Extinction of even one species, could result in the collapse of the entire ecosystem. Several models for population growth have been proposed to fit experimental data [19]. However these models are described at population level and not individual level. In individual-based modeling however, the population dynamics occur due to individual level reproduction and mortality.

As an example, we describe an individual-based version of the logistic growth model. The logistic model is one of the most widely used population growth model. The logistic equation in its discrete form describing the population dynamics as a function of population density is given by

$$N_{(t+1)} = N_t \cdot e^{\left\{r_0\left(1-\frac{N_t}{K}\right)\right\}} \tag{1}$$

where N_t and $N_{(t+1)}$ are population sizes at time t and $(t+1)$ respectively, K is the carrying capacity, and r_0 is the population growth rate. Carrying capacity is the maximum population an environment's available resources can sustain.

Using a first order approximation, Eqn. (1) can be simplified as

$$\frac{\Delta N_t}{N_t} = r_o\left(1 - \frac{N_t}{K}\right) \tag{2}$$

where ΔN_t is the change in population at time t which is the net sum of total births and deaths given by

$$\Delta N_t = \hat{b} \cdot N_t \cdot (1 - P_d)^m - N_t P_d \tag{3}$$

where $\hat{b}$ is the average number of offsprings per capita, P_d is the death rate and m is the maturity age beyond which an individual can reproduce. Using Eqns. (2) and (3), per capita births can be obtained as

$$\hat{b} = \frac{P_d}{(1-P_d)^m} \cdot \left(1 + \frac{r_o}{P_d}\left\{1 - \frac{N_t}{K}\right\}\right) \tag{4}$$

For the individual-based model which can produce population dynamics similar to the logistic equation, the parameter N_t (current population size) needs to be estimated by individual using information from their immediate vicinity. At every time step (t), each individual (i) can sense the number of individuals (including self) (n_t^i) with in an interaction area (I_{area}). We define observed density (o_t^i) as the ratio n_t^i/I_{area}. The average population density experienced by the individual, i, at time step t is therefore given by

$$d_t^i = d_{t-1}^i + \lambda\left(o_t^i - d_{t-1}^i\right) \tag{5}$$

where d_t^i is population density experienced by individual i at time t, o_t^i is the observed density at time step t, and λ is the update rate. The experienced population density of an individual at birth d_0^i is inherited from parent $p(i)$, so that

$$d_0^i = d^{p(i)} \tag{6}$$

We assume that the each individual has the knowledge of the desired equilibrium population density. This number is called genetic density G_d and is related to the carrying capacity K. Since, the local population density is sensed by each individual, the population dynamics similar to Eqn. (1) is achieved if the number of offsprings of an individual i, is given by

$$b_t^i = \begin{cases} P_b\left(1 + \alpha\left\{1 - \frac{d_t^i}{G_d}\right\}\right) & d_t^i < \frac{1+\alpha}{\alpha} G_d \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where b_t^i is the number of offsprings, α is the rate parameter and P_b is the birth rate such that

$$P_b = \frac{P_d}{(1-P_d)^m} \tag{8}$$

Figure 1 shows the population dynamics for different sizes of initial population. As seen from the figure, in all the cases, the population converges towards the desired population. Figure 2 shows the trend of the average population with the increase in desired population size ($G_d\times$World Area). An initial population of 3000 individuals on a square lattice of size 128×128 is used to generate the results. The advantage of modeling reproduction and mortality at individual-level is that they can be made more realistic by including simple rules like age-dependent mortality, seasonal variation in reproduction, fertility depending on the position in the group [34], among others.

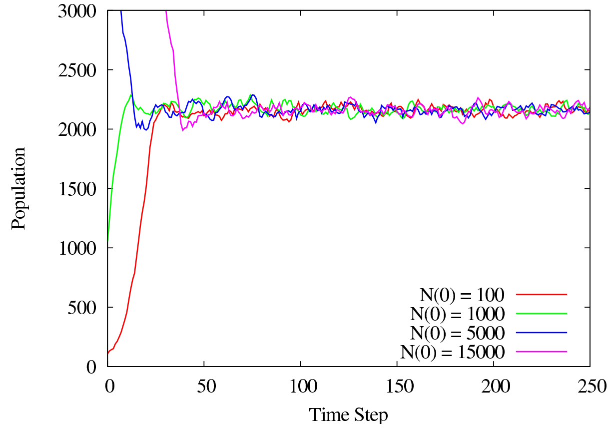

Figure 1: Population dynamics for various initial populations ($N(0)$). Result generated using P_d=0.2, λ=0.2, m=5, α=2 and G_d=0.122 (for a desired population of 2000).

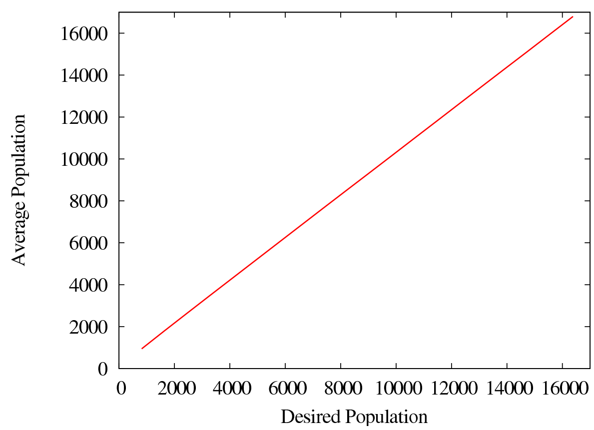

Figure 2: Trend of average population with desired population using the individual-based population model. Result generated using P_d=0.2, λ=0.2, m=5 and α=2.

Another important biological process is mobility. Mobility is demonstrated by living creatures for variety of reasons including seasonal migration, foraging for food, escape from predators, search for reproduction site, and search for mate. Several species form patterns while moving in groups. Examples of such patterns include flocking in birds, herding in cattle, schooling in fish, and trailing in ants. Several agent-based models [4, 32, 16] have demonstrated, that local interactions between individuals can result in such pattern forming. For the present work, only the case of random movement is considered.

Simple variations of the above biological processes are used in AES methodology to construct life-cycles of individuals and in turn the entire ecosystems capable of solving the desired problem. Given a design or optimization problem (referred to as problem from here on), a natural ecology model to which the problem can be mapped is selected. When mapping the problem to the ecosystem, the design parameter set, that needs to be optimized, is mapped as adaptable characteristics of one of the biological species. If more than one parameter set needs to be optimized, as in the case of multi-objective optimization problems, more than one species may have adaptable characteristics. Other specified parameters or information available about the problem are mapped to the environment. Finally, any modifications to the ecosystem that may increase computational efficiency without the loss of generality are applied. Having mapped the problem, the artificial ecology is simply allowed to evolve. We take inspiration from nature in assuming that any species that survive over time in the ecology would have adapted optimally to the environment and therefore, would have high levels of fitness.

3. ILLUSTRATIVE PROBLEM

To demonstrate the proposed modeling approach, we attempt to solve the problem of binary texture synthesis using an artificial predator-prey ecosystem. Given a random binary texture, we attempt to find the optimal Markov Random Field (MRF) parameter set capable of regenerating the input binary texture.

3.1 MRF Texture Models

Consider the image field S to be a $N \times N$ grid. Let $X(i,j)$ be the intensity level at point (i,j) on S. To simplify notation, $X(i,j)$ is written as x_{ij}. Let Λ be the colorspace from which the intensity of each location on S is drawn. For a binary texture Λ has only two elements, i.e., $\Lambda = \{-1, 1\}$. Let $\eta(i,j)$ be the first-order neighborhood [11] of the pixel x_{ij}. We consider S to a toroidal grid, so that each pixel has exactly four first-order neighbors. Unless an image/texture is random noise, the pixel intensity at any location depends on the intensities at other locations. If the conditional probability distribution function for a pixel depends only on the intensities of its neighboring pixels. i.e.,

$$P(x_{ij}|X) = P(x_{ij}|X(\eta(i,j))) \tag{9}$$

the image process is called a Markov Random Field. Markov Random Fields have been used extensively for texture synthesis [11, 18]. In the following, we use the popular anisotropic Ising MRF which is characterized by the energy function

$$U(X) = -\beta_1 \sum_{i\,j} x_{ij}x_{i(j+1)} - \beta_2 \sum_{i\,j} x_{ij}x_{(i+1)j} \tag{10}$$

where β_1 and β_2 are the parameters of the texture.

Given these parameters S is visited site-wise and the intensity of the current site $(i,\ j)$is set to -1 with probability $\propto exp\Big\{-\beta_1 \sum_{\overleftrightarrow{\eta(i,j)}} x_{ik} - \beta_2 \sum_{\updownarrow\eta(i,j)} x_{kj}\Big\}$, and to 1 with probability $\propto exp\Big\{\beta_1 \sum_{\overleftrightarrow{\eta(i,j)}} x_{ik} + \beta_2 \sum_{\updownarrow\eta(i,j)} x_{kj}\Big\}$, where $\sum_{\overleftrightarrow{\eta(i,j)}} x_{ik}$ denotes sum of intensities across horizontal neighbors, and $\sum_{\updownarrow\eta(i,j)} x_k j$ denotes sum of intensities across vertical neighbors. The resulting texture is an Ising MRF with parameters β_1 and β_2.

Given a binary texture image, the proposed methodology is used to estimate its MRF parameters, β_1 and β_2. These parameters are then used to synthesize the output textures. We require these output textures to be visually indistinguishable from the input texture.

3.2 Artificial Predator-Prey Ecosystem

A predator-prey ecosystem is considered for the illustrative problem. The artificial ecosystem consists of three components predators, preys and the environment. The texture whose parameters are to be estimated is mapped to the environment so that, the land cover is assumed to be the texture. The predator species is equipped with the ability to differentiate prey from the background (visual acuity) and kill them. The MRF parameters β_1 and β_2 are mapped as evolvable characteristics of the prey. Based on these parameters, each prey is born with a textured coat, which camouflages it against the environment. A prey, whose parameters are closer to those of the environment (original texture), get better camouflage, i.e., better protection from the predators. A prey that cannot be seen by the predator is said to have adapted to the environment.

The initial prey population parameters are initialized to random values. The preys pass these parameters (can be thought of as "genes") to offsprings with a small random mutation at a fixed mutation rate. The predator's seek and kill mechanism can therefore be thought of as a fitness function, albeit, a local one that is internal to the ecosystem.

Several modifications to the natural ecosystem were made to improve the computational efficiency. A large predator population means that even at low killing rates the prey might not have enough opportunity to adapt to the environment [27]. This would result in the extinction of prey population. Hence a small predator population with low killing rates is used. Since the predator does not have any parameters that need to be evolved, reproduction and death processes for predators do not contribute to the improvement of the system in anyway. Prey are given random movement so that probability of the prey staying in a given neighborhood is equal to the probability of leaving the neighborhood. Due to this random movement of the prey, predator mobility is not necessary for ensuring complete monitoring of the prey population. Therefore the predators are modeled to be immobile, immortal, and impotent, and are placed at strategic locations.

3.3 IBM Description

IBMs are essentially more complex in structure than analytical population-level models [31, 2]. Unlike population-level models, individual-based models take into account individual variability, and detailed behaviors of individual, increasing the number of variable parameters and the complexity of the model. This makes communication of results of an IBM via the familiar language of mathematics, unrealistic. To overcome this problem a standard protocol was proposed by Grimm *et.al.,* [32] to facilitate communication and replication of IBMs. The protocol was later revised [33] and named the ODD (Overview, Design Concepts, Detail) protocol. We adopt this protocol to describe the developed IBM.

3.3.1 Purpose

The model was developed to investigate the viability of artificial ecosystems to solve design and optimization problems. A modified predator-prey ecosystem is modeled using the bottom-up approach of individual-based modeling. We expect that the ecosystem processes - prey population dynamics and interactions between predators and prey will result in the solution of the desired problem of texture synthesis from a given binary texture image.

3.3.2 State variables and scales

The model consists of two species, predator and prey, and their environment. For each prey, age (in time steps), location in the environment and interactions with other prey are tracked. Each prey is born with certain texture endowing parameters β_1 and β_2 (genes) which determine the texture on its coat. Predators have no state variables. The environment is a 512×512 image of the texture whose parameters are to be estimated. The binary texture is made of 3×3 color cells with each cell representing a potential location for the predators or prey. Each cell is capable of housing more than one individual. The model operates in discrete time steps. At each step, prey are selected in random order, and their individual processes executed, after which predators are selected in a random order and their individual processes are executed. The simulation state is updated after each individual has completed their process, so that the next individual sees the updated simulation state. Figure 3 shows the simulation setup and examples of prey coats.

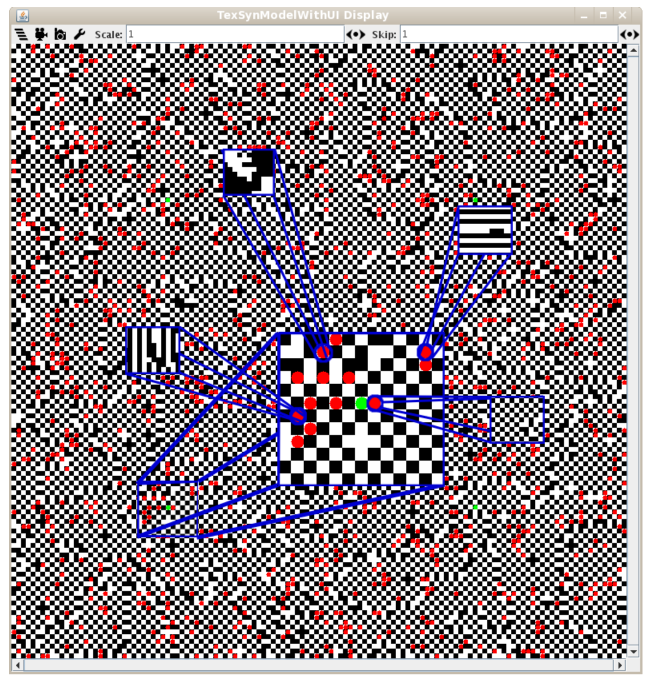

Figure 3: Simulation Model Setup. The red dots indicate prey, the green dots indicates predators. Each prey is endowed by genes (β_1, β_2) which project a textured coat. Four such texture coats are depicted in the image.

3.3.3 Process overview and scheduling

The model proceeds in discrete time steps. Within each time step, each prey is randomly selected and its processes are executed. Prey processes include interaction, movement, reproduction, and mortality, and are executed in the same order for each prey. The age of all prey alive at the beginning of a time step is incremented by one. In update interactions process, preys update their experienced population density using Eqn. (5). In the movement process, each prey moves to another location within a distance of *mobility* from the current location. During reproduction, prey older than *maturity age* reproduce with a probability of *birth rate* (Eqn. (8)). Every prey has the knowledge of the desired equilibrium population density (G_d). Each prey which reproduces at a given time step, produces number of offsprings as given by Eqn. (7).

Death of the prey due to natural reasons is modeled as an empirical rule describing it as a probability of *death rate*. In the mortality process, each prey rolls a dice to see whether it survives. If a prey dies, it is immediately removed from the simulation state.

The only predators process is killing prey. The predator calculates certain statistics about the local environment (land cover) and the coats of the prey within a distance of *predation radius*. The calculated statistics are defined as

$$dc = \frac{\sum_{i=1}^{L_s} \sum_{j=1}^{L_s} x_{ij}}{L_s^2} \tag{11}$$

$$f_x = \frac{\sum_{i=1}^{L_s} \sum_{j=1}^{L_s-1} bool(x_{ij} \mathrel{!=} x_{i(j+1)})}{L_s^2} \tag{12}$$

$$f_y = \frac{\sum_{i=1}^{L_s-1} \sum_{j=1}^{L_s} bool(x_{ij} \mathrel{!=} x_{(i+1)j})}{L_s^2} \tag{13}$$

where L_s is the length of side of the texture image in question and is equal to twice the predation radius for local environment, and is equal to size of the prey coat. The quantity x_{ij} is intensity value at location (i, j) and *bool* is an boolean function which return 1 if the condition is satisfied, and 0 otherwise. Therefore, *dc* represents the average gray value of the image, f_x represents the average number of pixel value changes from white to black and vice versa along the horizontal direction, and f_y represents the average number of pixel value changes from white to black and vice versa along the vertical direction.

Any prey whose coat texture is different than the texture of the environment would have different statistics than the environment. A predator is said to have spotted a prey against the environment if

$$\begin{aligned}(|E_{dc} - P_{dc}| > T_{dc})||(|E_{f_x} - P_{f_x}| > T_{fx})\\ ||(|E_{f_y} - P_{f_y}| > T_{fy})\end{aligned} \tag{14}$$

is satisfied, where E_* and P_* represent environment and prey coat statistics respectively. T_{dc}, T_{fx} and T_{fy} are the threshold for *dc*, f_x and f_y, respectively. Such a prey is said to be unadapted to the environment and can be caught by the predators. Although, for the present work these thresholds are selected empirically, it is possible to adapt these as parameters using an evolving predator population. The predator then randomly selects, one or more of the unadapted preys and kills it with a probability of *predator success rate*.

3.3.4 Design concepts

Emergence: Although the prey life cycle (movement, reproduction, and mortality) and predator behaviors (predation) are described by empirical rules and probabilities, the population dynamics, and prey adaptation emerge from the behaviors and interactions of the individuals.

Sensing: Both the predator and prey can be said to have visual perception. Prey use this type of sensing for interactions with other prey. Predators use visual information for predation. Also each prey is assumed to know its own age and reproduction capabilities.

Interactions: Two types of interactions are explicitly modeled. Interactions between two prey are used to keep track of number of other prey in vicinity. Predation is the second interaction modeled between a predator and a prey.

Stochasticity: Prey birth and death events, and predation success are modeled via probabilities, which add stochasticity to the model. To obtain more precise prediction values, each simulation is repeated 10 times, from which respective mean values are taken as representatives.

Observation: Prey population size, and number of adapted and unadapted prey (see Eqn. (14)) are recorded at the end of each time step. The adaptable parameters β_1 and β_2 of the entire prey population is recorded at the start of the simulation and at the end of the simulation.

3.3.5 Initialization

The environment is initialized to the given texture. N_{prey} prey are randomly placed in the environment, and their texture parameters randomly initialized. The maturity age (m) is obtained as

$$m = round\left\{\frac{0.25 \times 100}{P_d}\right\} \tag{15}$$

The age and observed density of the initial prey population are initialized as

$$p_a^i \sim U\{0, 3 \times m\} \tag{16}$$

$$d_0^i \sim possion\{(N_{prey}/A) \times I_{area}\}/I_{area} \tag{17}$$

where P_d is the prey natural death rate, $U(x, y)$ is a uniform random number generator, generating values from x to strictly $(y - 1)$, d_0^i is the observed density of i^{th} prey of the initial population, N_{prey} is the number of preys at the start of the simulation, A is the world area, I_{area} is the interaction area of an individual.

A number (N_{pred}) of predators are placed in strategic locations of the environment to maximize predator-prey interactions. Table 1 provides an overview and values of the parameters used in the model.

3.4 Results

Several agent-based modeling software are currently available [23]. For the following results, MASON [26], was used as the agent-based modeling environment.

Figures 4 and 5 show the results of experimental runs performed on texture shown in Figure 6(e). Figure 4 shows the prey population dynamics observed during one of the simulation runs and Figure 5 shows the values of prey parameters β_1 and β_2 at the start and end of a simulation run. Also shown in Figure 5 are mean of the parameter values of the final population for one run and the deviation of means over 10 such runs. At each time step, the predators report the number of total prey, adapted prey, and unadapted prey in their predation radius. As can be seen from Figure 4, the difference between the total prey counted externally and prey count reported by the predators is small. This validates the initial assumptions that a small immobile predator population is adequate to monitor the prey population.

From Figure 5 it can be seen that although the initial prey population parameters β_1 and β_2 were initialized with a wide range of random values, the final population parameter values clustered into a small parameter space, which can

Table 1: Overview and values of the parameters for the predator-prey model

Parameter	Value
Environment Parameters	
Habitat Width (cells) (W)	128
Habitat Height (cells) (H)	128
Display width (cells)	512
Display height (cells)	512
Input texture parameters (β_1, β_2)	
(For Texture 6a)	(-1, -1)
(For Texture 6c)	(1, -1)
(For Texture 6e)	(-1, 1)
Prey Parameters	
Initial number of prey (N_{prey})	1000
Initial prey location	randomly placed
Interaction radius (cells) (R_{prey})	10
Interaction area (cells). Number of cells in R_{prey}	317
Birth rate (%) (P_b)	(See Eqn. (8))
Death rate (%) (P_d)	20
Genetic density (G_d)	$\frac{N_{prey}}{(W \times H)}$
Mobility (cells) (P_m)	1
Mutation rate (%) ($P_{\mu r}$)	10
Mutation (P_μ)	± 0.1
Maturity age (time steps) m (See Eqn. (15))	3
Coat width (cells) (C_w)	$2 \times R_{prey}$
Coat height (cells) (C_h)	$2 \times R_{prey}$
Offsprings produced (b)	$\frac{\{G_d \times I_{area}\}}{\left\{\frac{P_i}{P_{age}}\right\}}$
Initial prey population age (p_a)	(See Eqn. (16))
Initial prey observed density (d_0)	(See Eqn. (17))
Initial prey coat parameters	
β_1	$U(-3, 3)$
β_2	$U(-3, 3)$
Predator Parameters	
Predator population (N_{pred})	4
Predator location	$(\frac{W}{4}, \frac{H}{4})$ $(\frac{W}{4}, \frac{3H}{4})$ $(\frac{3W}{4}, \frac{H}{4})$ $(\frac{3W}{4}, \frac{3H}{4})$
Predation radius (cells) R_{pred}	30
Predation success rate (%) (P_p)	50
Predation attempts (N_{kill})	1
Texture difference thresholds (T_{dc}, T_{fx}, T_{fy})	(0.05, 0.1, 0.1)

be considered as the solution space of the problem. Interactions between predators and prey are responsible for adapting the prey parameter values towards the solution space. A major part of the prey population is categorized as unadapted by the predators (Figure 4). However, the clustering of parameter values (Figure 5) suggests that the parameter values of the unadapted prey must differ from those of the adapted prey by an insignificant amount. The reported unadapted prey count, could be due to the high mutation and low predation rates used in the simulation. Due to the high mutation rate, there exists a significant probability that an adapted prey with parameters values near the boundary of the solution space could give birth to an unadapted prey. So potentially a cycle could form in which the interactions between predators and prey result in adapted prey and mutation in adapted prey give rise to unadapted prey. The study of this possible emergent phenomenon is however not of interest to the current work and is left as a problem for further investigation.

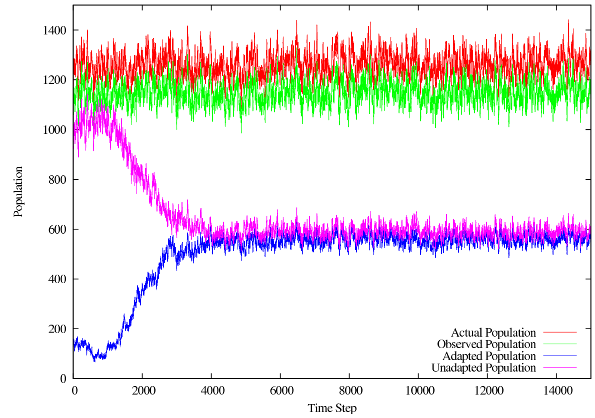

Figure 4: Prey population dynamics observed during one simulation run for texture in figure 6(e)

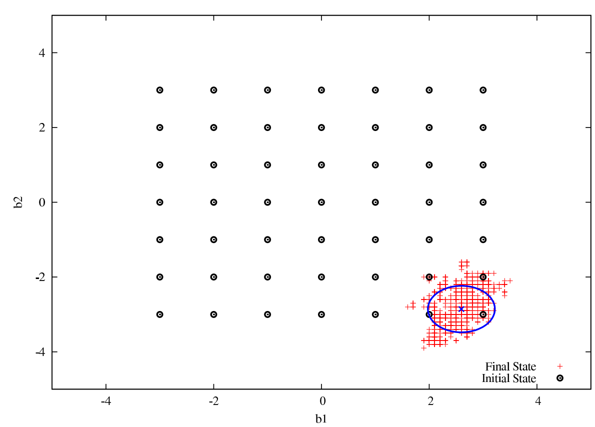

Figure 5: Prey adaptation: scatter plots of prey parameters for texture in Figure 6(e); black dots indicate the parameter values of the initial population and red dots indicate the parameter values of the final population. The blue dot is the mean of the current run and the radius of the blue circle is the standard deviation of means over 10 runs.

Figure 6 shows the results of texture synthesis with the parameters estimated using AES. The output textures in Figure 6 are synthesized using the average parameter values of the final prey population. In all the cases the statistics of the input texture were well captured by the model and there is little if any visual difference between the original and synthesized images.

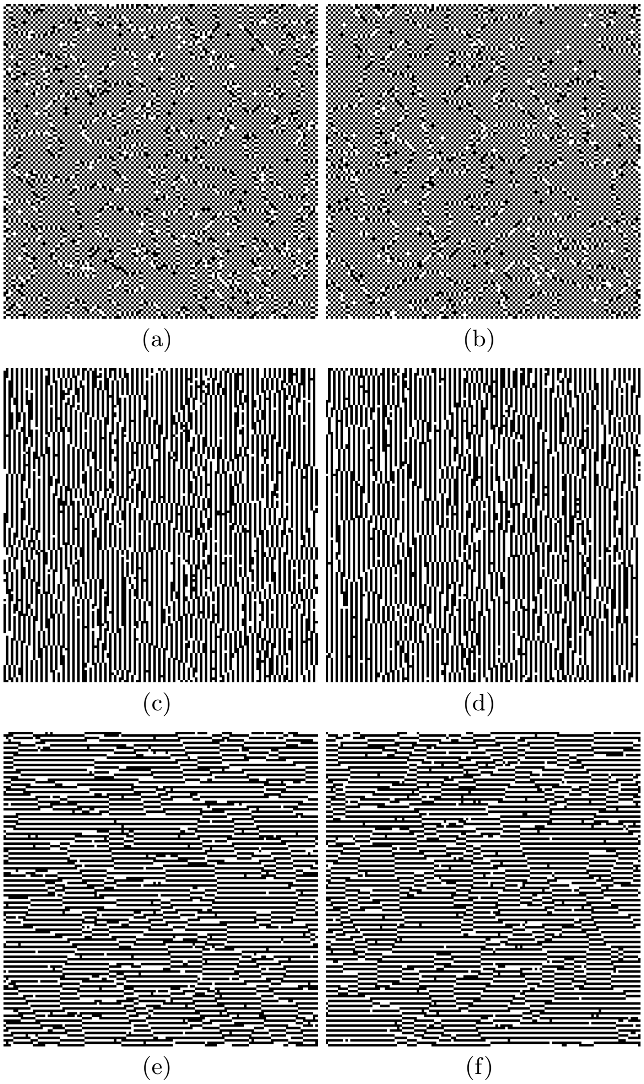

Figure 6: Texture synthesis results: *a*, *c*, and *e* are original textures (input); *b*, *d*, and *f* are synthesized textures (output).

4. CONCLUSIONS

In this paper, we proposed an individual-based design and optimization methodology, inspired by natural ecosystems. A detailed description of the approach was presented. Essential details of population level biological processes and their individual level counterparts were discussed. A simple, yet classical problem of binary texture synthesis was attempted to demonstrate the efficacy of the proposed methodology. The problem was mapped to an artificial predator-prey ecosystem. An IBM of the ecosystem was developed and experimental runs were performed. The results demonstrate the paradigm's ability to solve design and optimization problems. We believe this approach can address many complex problems found in various industries such as the unit commitment problem, design of flexible manufacturing systems, process and resource planning and scheduling. We are currently exploring this approach for image segmentation and terrain analysis in airborne images. Other potential areas of research include identifying other natural ecosystems, which can be used with the proposed approach and investigating unanticipated emergent phenomena in the developed models.

5. ACKNOWLEDGMENTS

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6. REFERENCES

[1] A. Hastings. *Population Biology. Concepts and Models.* Springer-Verlag, New York, New York, USA, 1997.

[2] B. Breckling, U. Middelhoff, and H. Reuter. Individual-Based Models as Tools for Ecological Theory and Applicatioin: Understanding the Emergence of Organisational Properties in Ecological Systems. *Ecological Modelling*, 194:102–113, 2006.

[3] B. C. Harvey and S. F. Railsback. Elevated Turbidity Reduces Abundance and Biomass of Stream Trout in an Individual-Based Model. Draft manuscript, U. S. Department of Agriculture, Redwood Sciences Laboratory, Arcata, CA, 2004.

[4] C. W. Reynolds. Flocks, Herds, and Schools: A Distributed Behavior Model. *Computer Graphics*, 21(4):25–34, 1987.

[5] D. E. Goldberg. *The Design of Innovation.* Kluwer Academic Publishers, Massachusetts, USA, 2002.

[6] D. Helbing, I. Farkas, and T. Vicsek. Simulating Dynamical Features of Escape Panic. *Nature*, 407:487–490, 2000.

[7] D. J. T. Sumpter and D. S. Broomhead. Relating Individual Behavior to Population Dynamics. In *Proceedings: Biological Sciences*, volume 268, pages 925–932, 2001.

[8] D. L. DeAngelis and W. M. Mooij. Individual-Based Modeling of Ecological and Evolutionary Processes. *Annual Review of Ecology, Evolution, and Systematics*, 36:147–168, 2005.

[9] E. Bonabeau. Agent-Based Modeling: Methods and Techniques for Simulating Human Systems. In *Proceedings of National Academy of Sciences, USA, Vol. 99, Suppliment 3*, pages 7280–7287, 2002.

[10] G. Huse, S. Railsback, and A. Ferno. Modelling Changes in Migration Pattern of Herring: Collective Behavior and Numerical Domination. *Journal of Fish Biology*, 60:571–582, 2002.

[11] G. R. Cross and A. K. Jain. Markov Random Field Texture Models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 5(1):25–39, Jan. 1983.

[12] J. Chen, H. Liu, and X. Zhang. Primary Study on MAS-based Single Species Ecosystem Model. In *1st International Symposium on Pervasive Computing and Applications*, pages 300–305, 2006.

[13] J. D. Sterman. Systems Dynamic Modeling: Tools for Learning in a Complex World. *California Management Review*, 43(4):267–284, 2001.

[14] J. M. Epstein and R. L. Axtell. *Growing Artificial Societies: Social Science from the Bottom Up*. The MIT Press, Nov. 1996.

[15] J. V. Neumann. *Theory of Self-Reproduction Automata*. University of Illinois Press, Urbana, Illinois, USA, 1966.

[16] L. Panait and S. Luke. Ant Foraging Revisited. In *Proceedings of the Ninth International Conference on the Simulation and Synthesis of Living Systems*, pages 569–574, 2004.

[17] M. Granovetter. Threshold Models of Collective Behavior. *The American Journal of Sociology*, 83(6):1420–1443, 1978.

[18] P. Perez. Markov Random Fields and Images. *CWI Quarterly*, 11(4):413–437, 1998.

[19] P. Turchin. *Complex Population Dynamics: A Theoretical/Empirical Synthesis*. Princeton University Press, 2003.

[20] R. Axelrod. *Evolution of cooperation*. Basic Books, New York, New York, USA, 1984.

[21] S. C. Bankes. Agent-Based Modeling: A Revolution? In *Proceedings of the National Academy of Sciences of the USA*, volume 99, pages 7197–7198, 2002.

[22] S. Eubank, H. Guclu, V. S. A. Kumar, M. V. Marathe, A. Srinivasan, Z. Toroczkai, and N. Wang. Modelling Disease Outbreaks in Realistic Urban Social Networks. *Nature*, 429:180–184, 2004.

[23] S. F. Railsback, S. L. Lytinen, and S. K. Jackson. Agent-Based Simulation Platforms: Review and Development Recommendations. *Simulation*, 82:609–623, 2006.

[24] S. G. Eubank. What Makes a Simulation Useful? [TRANSIMS]. In *Proceedings of 1999 IEEE International Conference on Systems, Man, and Cybernetics*, volume 4, pages 640–644, 1999.

[25] S. I. Nishimura and T. Ikegami. Emergence of Collective Strategies in a Prey-Predator Game Model. *Artificial Life*, 3:243–260, 1997.

[26] S. Luke, C. Cioffi-Revilla, L. Panait, and K. Sullivan. MASON: A Multiagent Simulation Environment. *Simulation*, 81:517–527, 2005.

[27] S. S. Vulli. Individual-Based Artificial Ecosystems for Design and Optimization. Master's thesis, Missouri University of Science and Technology, Mar. 2008.

[28] S. Wolfram. *A New Kind of Science*. Wolfram Media, Inc, 2002.

[29] T. A. Kohler, G. J. Gumerman, and R. G. Reynolds. Simulating Ancient Societies: Computer Modeling is Helping to Unravel the Archaelogical Mysteries of the American Southwest. *Scientific American*, pages 76–83, July 2005.

[30] T. C. Schelling. *Micromotives and Macrobehavior*. W. W. Norton, New York, New York, USA, 1978.

[31] V. Grimm. Ten Years of Individual-Based Modelling in Ecology: What Have We Learned and What Could We Learn in the Future? *Ecological Modelling*, 115:129–148, 1999.

[32] V. Grimm and S. F. Railsback. *Individual-based Modeling and Ecology*. Princeton Series in Theoretical and Computational Biology. Princeton University Press, 2005.

[33] V. Grimm et al. A Standard Protocol for Describing Individual-Based and Agent-Based Models. *Ecological Modelling*, 198:115–126, 2006.

[34] W. C. Pitt, P. W. Box, and F. F. Knowlton. An Individual-Based Model of Canid Populations: Modelling Territoriality and Social Structure. *Ecological Modelling*, 166:109–121, 2003.

[35] Y. Bar-Yam. *Dynamics of Complex Systems*. Addison-Wesley, USA, 1997.